Data Science in Finance and Economics

DSFE, 6(2): 315–335.
DOI: 10.3934/DSFE.2026011
Received: 20 October 2025
Revised: 16 April 2026
Accepted: 17 April 2026
Published: 01 June 2026

http://www.aimspress.com/journal/dsfe

Research article

Introduction of the HC-LVQ artificial neural network for the optimization of Mexican financial cycle indicators and the identification of their turning points in real time

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Abstract: The High-Coverage Learning Vector Quantization Artificial Neural Network introduced in this paper is a non-parametric supervised classification machine learning algorithm closely related to the Vector Quantization Method and is based on the LVQ Artificial Neural Network presented by Kohonen in 2001. The HC-LVQ method is a novel approach for identifying turning points in real-time in the Mexican financial cycle based on the Mexican Stock Exchange (MXX) by optimizing a set of four key financial indicators from a selection of global stock market indices. It proved to be a competitive method compared to other traditional methods in identifying the turning points ahead of the Bry-Boschan algorithm (1971) by pinpointing in advance all the bear points (peaks) in the test period, from January 2006 to January 2024. Specifically, the HC-LVQ anticipated the identification of the Mexican financial cycle's bear of the Subprime crisis by 5 months, signaling it in May 2007 and the bull (trough) in August 2008. In contrast, the System of Composite Indicators Coincident and Advance of the National Institute of Statistics and Geography of Mexico identified the peak of the Subprime crisis for the Mexican business cycle in April 2008 and in June 2009 its recovery; while the NBER identified the peak of the Subprime crisis of the U.S. business cycle in December 2007 and in June 2009 its trough. The HC-LVQ identified the Chinese HANG SENG, the German DAX 40, the

Brazilian BOVESPA, and the SPIPSA of Santiago de Chile as the indices' set that best helped identify the turning points of the MXX.

Keywords: financial cycles; risk aversion; financial crises; business cycles; economic crises; HC-LVQ artificial neural network; LVQ artificial neural network; VQ method; Bry-Boschan algorithm

JEL Codes: C610, C630, F370, G170, Y100

1. Introduction

The need to study the Mexican financial cycle has been increasing, particularly due to the effects on the Mexican economy resulting from the dynamics of its financial sector and from its interaction with the global financial cycle[1]. Moreover, the literature on the subject remains scarce, and its multidisciplinary origin has prevented reaching a well-established consensus, which makes it difficult to provide an exact definition of financial cycles. However, as mentioned by Schüler et al. (2020), they can be considered common fluctuations in the credit, real estate, and stock markets.

Furthermore, the importance of financial cycles in the evolution of the global Economy has been highlighted after the last dot-com crisis of 2001 and the Subprime turmoil of 2008[2], both originating in the US financial markets, and the Covid-19 crisis of 2020, although it did not have a financial origin, it brought harsh repercussions on the global economy and a major impact on the world's financial markets, emphasizing that the genesis of crises is multifaceted in nature and that they can spread rapidly between countries and regions of the world. Despite this, recognizing and describing the interactions between the financial sector and the real economy is a complicated task even in developed countries, with most of the literature on the subject coming mostly from the United States and some European countries, including the United Kingdom, Germany, France, the Netherlands, and Denmark, which have a long financial tradition.

Despite the fact that the US financial sector has dictated global financial sector guidelines for decades, the Chinese financial sector seems to be replacing or alternating it, becoming the biggest world economic power in 2024 in terms of the adjusted GDP, with a 19% share compared to 15.2% for the United States. This represents a different global landscape in the coming decades, especially for Mexico due to its strategic position between these two powers[3]. This, added to the geopolitical context and the decoupling of the US economy from China, due to the Trade War that has pitted them

[1] The existence of a global financial cycle and its interaction with the financial cycles of the countries has been highlighted in the literature by authors such as Claessens et al. (2011a, 2021b). Grinderslev et al. (2017) note that, generally, medium-term business cycles in the United States lead to medium-term cycles in other countries, which can be seen as the global cycle.
[2] The *Subprime* crisis occurred between 2007 and 2009 according to US NBER (National Bureau Economic Research).
[3] Corneli et at., (2023) provided evidence of the increasingly important role of China in the global business cycle through an analysis of the impact of news from the Chinese economy (associated with global trade and industrial production) on stock markets and commodity prices, especially in emerging countries, including Mexico. This coincides with the Mexican conjuncture derived among other reasons, from the China-United States trade war initiated in 2018 and the more relevant role of Mexico in the supply chain of both countries. In the first quarter of 2024, Mexico surpassed China as the main supplier of products to the United States, where the latter participates in more than three quarters of Mexican exports, 82.9%, and in imports 41.4%. China, on the other hand, represents 20% of registered Mexican imports, according to Mexican government data, available on the official website of the Ministry of Economy: https://www.gob.mx/se/

against each other since 2018 and has intensified since January 2024 during Donald J. Trump's second term as President of the United States. Recently, President Trump has added Mexico to the fray, which has created a turning point for that country.

Furthermore, in Mexico and South America, where financial sectors are particularly vulnerable due to weak banking systems, fragile stock markets, or greater exposure to volatility in capital flows, the lack of data makes it more difficult to study financial cycles and increases not only the need for such studies but also the generation, recognition, and storage of data on financial variables. In contrast to the classical approach to studying financial cycles, we explore the behavior of the Mexican financial cycle by introducing the High-Coverage Learning Vector Quantization Artificial Neural Network, simply called HC-LVQ, for identifying turning points in real-time in the Mexican financial cycle based on the Mexican Stock Exchange (MXX) by optimizing a set of four key financial indicators[4] from a selection of twelve stock market indices: three from North America, four from Europe, three from Southeast Asia, and two from South America[5].

The HC-LVQ algorithm proved to be a competitive method compared to other traditional methods in identifying the turning points in the Mexican financial cycle, outperforming the Bry-Boschan algorithm (1971), which follows the Burns and Mitchel (1946) methodology for identifying turning points in individual time series by anticipating all *bear* (peak) points in the test period. In particular, HC-LVQ identified the *bear* of the *Subprime* crisis five months in advance, signaling it in May 2007, and the *bull* (trough) in August 2008. The HC-LVQ confirmed that the *bear* of the Subprime crisis in Mexico preceded the peak of the economic crisis, as the SICCA indicates the peak of the Mexican business cycle in April 2008 and its recovery in June 2009; while the NBER identified the peak of the *Subprime* crisis in the US business cycle in December 2007 and the trough in June 2009.

The HC-LVQ Artificial Neural Network identified the Chinese HANG SENG, the German DAX 40, the Brazilian BOVESPA, and the SPIPSA from Chile, as the key indices' set that best helped identify the turning points of the Mexican financial cycle, which coincide according to data from April of this year from the Mexican Government with being Mexico's third, fourth, and seventh largest trading partners in the world, respectively; while Chile is Mexico's fourth largest trading partner in South America, behind only Brazil, Colombia, and Peru. This confirms the importance and influence of the financial sectors of its major trading partners on the dynamics of the Mexican financial sector, where foreign trade represented 73,16% of Mexico's Gross Domestic Product (GDP) in 2023, according to the latest data from the World Bank.

[4] The number 4 of time series (indices or indicators) taken into account in this paper follows the indications of Giusto and Piger (2014), who recommended having 4 indicators for the implementation of the LVQ, arguing that it is the same number of indicators used by the NBER.

[5] Three from North America: the NASDAQ Composite, the NYSE Composite and the S&P 500 in the United States, four from Europe: the IBEX 35 in Spain, the CAC 40 in France, the DAX in Germany, and the FTSE 100 in the United Kingdom. Three indices were considered from Asia: Japan's NIKKEI225, China's HANH-SENG, and South Korea's KOSPI. Two South American indices were considered: Brazil's BOVESPA and Chile's SPIPSA. For the selection of these indices, the indices of the countries that have the greatest commercial relevance with Mexico were considered, and also whose data were available.

These results emphasize China's increasingly prominent role in Mexican business cycles, suggesting the existence of an intrinsic interconnection between the national financial sector and the major stock markets of its most important trading partners. In the case of South American indices, this could suggest an intrinsic interconnection between the financial sectors[6]. It should be noted that other important trading partners in the region, including Peru, Colombia, and Mexican countries in Central America, were excluded from the analysis due to a lack of data, including computational limitations that prevented the inclusion of at least the main index for each of Mexico's twenty major trading partners.

The HC-LVQ has computational advantages inherited and optimized from the LVQ method over parametric methods that have been frequently used to identify business cycles' turning points based on a set of coincident indicators[7]. Moreover, it is very easy to implement, and a large number of indicators can be incorporated, even with reports of different frequencies. The HC-LVQ method is, by its origin, a method to solve statistical classification problems such as the one presented in this paper, which, added to the results obtained here, makes it a method not only attractive but competitive in any area and not only in Finance or Economics, where a problem can be reduced to a statistical classification problem. In this study, we focus on the Mexican financial cycle, but it is easy adaptable to other economies, extending to different financial systems.

2. Methodology

The High-Coverage Learning Vector Quantization Artificial Neural Network introduced in this paper is a non-parametric supervised classification machine learning algorithm[8]. It is named HC-LVQ because it is based on the LVQ Artificial Neural Network presented by Kohonen in 2001 and was used for the first time in Economics by Giusto and Piger in 2014. Additionally, it is closely related to the Vector Quantization method and called High-Coverage (HC) since it seeks to cover a wide range of sets of parameters of the LVQ method and of the Mexican financial cycle indicators, with the objective of optimizing these sets for the early identification of their turning points,highlighting the relevance of

[6] Claessens et al. (2011a, 2011b) emphasized that business cycles often show a greater degree of synchronization with financial cycles associated with credit and the real estate market in the United States and other developed countries, while in emerging countries such as Mexico, they show a greater degree of synchronization with financial cycles associated with the stock market.

[7] As mentioned by Giusto and Pieger (2014), many of the researchers interested in identifying business cycle turning points have focused on parametric statistical models to link the observed data to the classes. For example, it is very common to use Benchmark models, including the Autoregressive model and Multivariate time series model, Tree-based models, or the Markov-switching method (DFMS), as mentioned by Aldasoro et al (2025). In the absence of the true data generating process (DGP), non-parametric methods may be more robust, as they do not rely on a specification of the DGP. Of particular interest are non-parametric classification techniques based on machine learning algorithms, which have been successfully utilized for real-time classification in many studies outside Economics and Finance.

[8] Supervised classification algorithms are those that require data with a prior label or classification, as opposed to unsupervised algorithms. Non-parametric algorithms are those that do not presuppose the specific form of the model to be generated for training, which makes them more flexible than their parametric counterparts; however, they require much more data for training.

the non-classical approach to the analysis of business cycles. The HC-LVQ method is, by its origin, a method for solving statistical classification problems such as the one presented in this paper, which, together with the results obtained herein, makes it not only an attractive method but also a competitive one in any area, not only in Finance and Economics, but also where a problem can be reduced to one of statistical classification.

The HC-LVQ Neural Network is an optimization of Kohonen's LVQ Neural Network (2001). In each implementation explained below, it performs, in turn, nCr implementations of the LVQ, where n is the total number and r is the target number of indicators. These parameters can be varied and large depending on the area of study in which it is used and the problem being addressed, although this increases the computational cost exponentially. Despite the fact that the HC-LVQ method, like the LVQ, is a method for statistical classification, its sole purpose is to define a series of class regions in the input data space and then choose the implementation that best classifies the data in the *test period* (defined as the period of time where the data needs to be classified, which runs from January 2006 to January 2024) by statistical discrimination using the Classification Accuracy (ACC)[9], which is simply the classification accuracy rate.

As noted by Kohonen (2001), to define these regions in each LVQ implementation, a subset of data, known as *codebook vectors* or *neurons*, is established. These *neurons* are classified similarly within each class region. In this type of algorithm, these *neurons* can be created and remain within each class region. Although the problem of optimal decision or statistical pattern recognition is addressed within Bayesian theory, the HC-LVQ approach is based on the philosophy of LVQ, which is fundamentally different, as described below.

Before describing the HC-LVQ method, it is necessary to specify that in this paper, following the algebraic notation on the *Matlab Neural Network Toolbox* 4 user guide Demuth (2004), vectors are written with a capital letter in italics and bolded. Column-vectors will have a subscript on the right: "$\boldsymbol{I}_m$", while row-vectors will have a subscript on the left: "${}_{i}\boldsymbol{IW}(\boldsymbol{i})$". Matrices will not have subscript, except when emphasizing their dimension: "$\boldsymbol{I}_{N\,x\,12}$". Functions will be denoted by capital letters: "C" or Greek letters: "β", and in other cases they will be named explicitly: "‖ndist‖ function". Finally, numbers will be denoted by capital or lowercase letters, but both in italics: "*r*", "*K*".

The HC-LVQ takes, as inputs, the historical monthly data for the last thirty years, from January 1993 to January 2024, from a selection of $m = 12$ global stock market indices mentioned above, constructing $\boldsymbol{I}_{N\,x\,12}$ (see arrangement 2.1), where $N = 373$ is the number of monthly samples for the complete study period, and whose column-vectors inputs $\{\boldsymbol{I}_m\}_{m=1}^{12}$ correspond to each of the N-monthly historical data points for each of the selection of 12 stock market indices, covering the *Tequila effect* crisis in 1994, the *dot-com* crisis in 2001, the *Subprime* crisis in 2008, and the *Covid-19* turmoil

[9] The percentage of correct answers is the Accuracy Rate. This is obtained by dividing the number of correct answers, corresponding to the number of true positives (T_p), in particular for this paper, the correctly classified Bull points, plus the number of true negatives (T_n), the correctly classified Bear points, by the total number of periods evaluated, and then multiplying by 100 to obtain a percentage. Although this measure is straightforward, it gives an overall idea that is easier to visualize.

$$ACC = \left(\frac{T_n + T_P}{N}\right) \cdot 100\%$$

in 2020. It also took the monthly historical data from the MXX represented by $\boldsymbol{MXX}_{N\,x\,1}$and its Bry-Boschan classifications[10] given by $\boldsymbol{K}_{N\,x\,1}$ in the same period. It should be noted that this study period was used with the aim to forecast the onset of the *Subprime* crisis. The use of MXX data prior to the Tequila effect in 1994 is not recommended, as this crisis was caused by the devaluation of the Mexican peso and the lack of international reserves to cover debt obligations.

$$\mathbf{I}_{\mathrm{Nx1}} = \begin{bmatrix} \mathbf{I}_{1,1} & \cdots & \mathbf{I}_{1,\mathrm{N}} \\ \vdots & \ddots & \vdots \\ \mathbf{I}_{\mathrm{N},1} & \cdots & \mathbf{I}_{\mathrm{N,N}} \end{bmatrix} \dots \quad (2.1)$$

The HC-LVQ considers four positive integers as parameters: $\mathrm{r}, \mathrm{K}, \ \mathrm{L}, \ \mathrm{G} \in \mathbb{Z}^{++}$. L is an even number defined as the number of neurons; G is the number of epochs, K is the number of classes, and $\mathrm{r} = 4$ is the number of key stock market indexes. In this paper, $\mathrm{K} = 2$, two classes (bull cycle = 1 or bear cycle = 0). Notice that it could be possible to incorporate a greater number of classes and stock market indexes or a different number r could be chosen, but this would increase the computational complexity of the HC-LVQ[11]. Finally, the neural network considered the *weight function* defined as: $\beta(g) = \frac{1}{g}$, where β: $\mathbb{Z}^{++} \longrightarrow (0,1]$, which represents the learning rate. Then, then the next steps were followed:

Step 1. This first step, whose outline can be seen below in Figure 1, was performed by function C, and the matrix $\boldsymbol{I}_{N\,x\,12}$ was confronted with the vector $\boldsymbol{K}_{N\,x\,1}$ of Bry-Boschan classifications of the MXX in the same time period to construct matrix $\boldsymbol{X}_{Nx13}$ (see arrangement 2.2)[12], which was constructed, in turn, by the of N-data row-vectors $\{_{nx12}\boldsymbol{X}\}_{n=1}^{N}$.

$$\boldsymbol{X}_{Nx13} = [\boldsymbol{I}_{Nx1}, \dots, \boldsymbol{I}_{Nx12}, \boldsymbol{K}_{Nx1}] = \begin{bmatrix} \boldsymbol{X}_{1,1} & \cdots & \boldsymbol{X}_{1,13} \\ \vdots & \ddots & \vdots \\ \boldsymbol{X}_{N,1} & \cdots & \boldsymbol{X}_{N,13} \end{bmatrix} \dots \quad (2.2)$$

Step 2. Performed by the D function, this step split $\boldsymbol{X}_{Nx13}$ into two time periods. The first period: The *training period*, from January 1993 to December 2005, to construct $\boldsymbol{X1}_{N'x\,13}$, where $N' = 156$. The second period: The *test period*, from January 2006 to January 2024, to construct $\boldsymbol{X2}_{N''x\,13}$, where $N'' = 217$. It should be noted that N' and N'' are the number of sample months for the first and second time periods, respectively. The outline of *step 2* is shown below in Figure 1.

[10] Its classification can be *bear cycle* = 0 or *bull cycle* = 1. The beginning to the end of each expansion period is defined as *bull cycle or bull market*, while from beginning to the end of each recession period is defined as the *bear cycle* or *bear market* of a financial cycle. The beginning and end of each *bull cycle* and *bear cycle* of the MXX and the other twelve selected time series were obtained via the Bry-Boschan algorithm (1971).

[11] The complexity of an algorithm is a measure of how much time and memory space it requires to produce a solution.

[12] Whose thirteen column-vector corresponds to the Bry-Boschan classifications of the N-data vectors $\{_{nx12}\boldsymbol{X}\}_{n=1}^{N}$. It can be seen that, by construction, the first 12 column-vectors of X were constructed by each of the time series of the initial selection of 12-stock market indices.

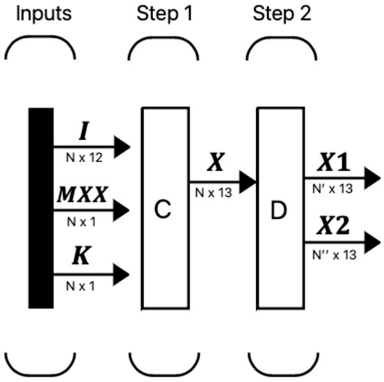

Figure 1. Diagram showing steps 1 and 2, which together produce $\boldsymbol{X1}$ and $\boldsymbol{X2}$ corresponding to the first and second time periods, respectively. Source: own work. Consistent with the representation of transfer functions used in the Matlab Neural Network Toolbox 4 user guide. Demuth (2004).

Step 3. This step consists of a competitive layer called *class training* and a linear layer called *class assignment*. Column-vectors were constructed, defined as: $\boldsymbol{K1}_{N'x\,1} = \boldsymbol{X1}_{13}$ and $\boldsymbol{K2}_{N''x\,1} = \boldsymbol{X2}_{13}$, then making c = 1, and generating $\boldsymbol{X1^c}_{N'x\,r}$ and $\boldsymbol{X2^c}_{N''x\,r}$ (r = 4), whose column vectors are: $\{\boldsymbol{X1^c}_r\}^4_{r=1} = \boldsymbol{X1}_{C(c,r)}$ and $\{\boldsymbol{X2^c}_r\}_r{}^4{}_{=1} = \boldsymbol{X2}_{C(c,r)}$, where $\boldsymbol{C}_{c\,x\,r}$ is the matrix of combinations of $\binom{m}{r}$. It can be seen that the vector of Bry-Boschan classifications corresponding to $\boldsymbol{X1^c}_{N'x\,r}$ and $\boldsymbol{X2^c}_{N''x\,r}$ is the vector $\boldsymbol{K1}$ and $\boldsymbol{K2}$ of the first and second time periods, respectively.

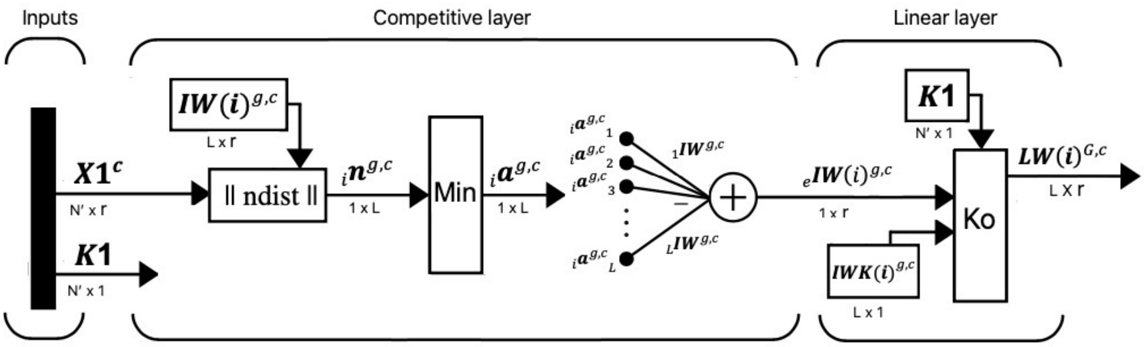

Figure 2. General outline of class training. Class training has a competitive layer and a linear layer. Source: Own elaboration and consistent with the representation of transfer functions used in the MATLAB Neural Network Toolbox 4 user's guide, Demuth (2004).

Next, *class training* was implemented, whose general scheme is shown in Figure 2, for the data matrix $\boldsymbol{X1}^c$ and $\boldsymbol{K1}$. In *class training*, it was constructed in the same R^r space of the $\boldsymbol{X1}^c$ row-vectors and randomly a set of L row-vectors named *neurons* $\{\{{}_l\boldsymbol{IW}(\boldsymbol{i})\}_{l=1}^{L}\}^{g,c}$ constructed $\boldsymbol{IW}(\boldsymbol{i})^{g,c}$, where $K < L < N'$ and whose classifications[13] in the set $\{bull$ cycle = 1 $bear\ cycle$ = 0$\}$ are known and represented by the column vector $\mathbf{IWK(i)}^{\mathrm{g,c}}_{\mathrm{L\,x\,1}}$. Ipso facto, the initial *neuron* locations

[13] Half were classified as *bull* =1 and the other half as *bear* =0.

$\{\{_l\boldsymbol{IW(i)}\}_{l=1}^{L}\}^{g,c}$were adjusted, obtaining a new matrix of *neurons*: $\boldsymbol{LW(i)}^{G,c} = \{\{_l\boldsymbol{LW(i)}\}_{l=1}^{L}\}^{G,c}$. This *neuron* location adjustment was performed through the following steps, as proposed by Giusto and Piger for the LVQ method in 2014, using the Euclidean metric, as it is the dominant metric in the literature:

Step (i). It made $g = 1$ and $i = 1$.

Step (ii). The *neuron* $_e\boldsymbol{IW}(i)^{g,c}$ closest to $_i\boldsymbol{X1^c}$ was identified, where $e = \arg \min_l \{||_i\boldsymbol{X1}^c - \{_l\boldsymbol{IW(i)}^g\}^c\ ||\}, l \in \{1, \dots, L\}$. This was done, first, by creating the vector $_i\boldsymbol{n}^{g,c}$ of distances, through the ||ndist|| function, and then finding, by the function Min, the minimum input of $_i\boldsymbol{n}^{g,c}$, which was replaced by 1 and the rest by 0 to construct $_i\boldsymbol{a}^{g,c}$. This vector was multiplied by the right-hand to $\boldsymbol{IW(i)}^{g,c}$ obtaining the *neuron* $_e\boldsymbol{IW(i)}^{g,c}$ closest to $_i\boldsymbol{X1}^c$.

Step (iii). It adjusted the location of $_e\boldsymbol{IW(i)}^{g,c}$ by the Ko function, obtaining $\boldsymbol{LW(i)}^{g,c}$ according to Kohonen's rule (2001):

$$\begin{cases} _e\boldsymbol{LW(i)}^{g,c} = {}_e\boldsymbol{IW(i)}^{g,c} + \beta^g[_i\boldsymbol{X1}^c - {}_e\boldsymbol{IW}(i)^{g,c}] \\ \text{if } _i\boldsymbol{X1}^c \text{ and } _e\boldsymbol{IW}(i)^{g,c} \text{ belong to the same class,} \\ \\ _e\boldsymbol{LW(i)}^{g,c} = {}_e\boldsymbol{IW(i)}^{g,c} - \beta^g[_i\boldsymbol{X1}^c - {}_e\boldsymbol{IW}(i)^{g,c}] \text{ otherwise.} \end{cases}$$

Step (iv). If $i + 1 \le N'$, it made $i = i + 1$ and repeated step (ii). Otherwise, it made $i = 1$ and $g = g + 1$, and if $g \le G$, it was seconded from step (ii); stopped if not.

In summary, in *class training*, in each iteration of g, the matrix $\boldsymbol{X1}^c$ and the vector $\boldsymbol{K1}$ were considered. Then, in each iteration of i, it was identified the closest *neuron* $_e\boldsymbol{IW(i)}^{g,c}$ to $_i\boldsymbol{X1}^c$, and if this neuron had the same classification as $_i\boldsymbol{X1}^c$, its location was moved closer to it; if the selected *neuron* $_e\boldsymbol{IW}(i)^{g,c}$ did not classify it correctly, then it was moved further away from it. At the end of the iterative process of i, a set of *neurons* $\boldsymbol{LW(N')}^{g,c} = \{\{_l\boldsymbol{LW(N')}\}_{l=1}^{L}\}^{g,c}$ was obtained, then at the end of the iterative process of g, a new set of *neurons* $\boldsymbol{LW(N')}^{G,c} = \{\{_l\boldsymbol{LW(N')}\}_{l=1}^{L}\}^{G,c}$ was obtained.

After *class training*, using the B function, neurons of $\boldsymbol{LW(N')}^{G,c}$ that did not change location were discarded to construct the matrix of neurons $\boldsymbol{LW(N')}^{F,c} = \left\{\{_l\boldsymbol{LW(N')}\}_{l=1}^{L'}\right\}^{F,c}$, which were considered *trained neurons* and whose classifications were given by $\boldsymbol{LWK(N')}_{L'x\,1}^{F,c}$, constructed by the inputs of $\boldsymbol{IWK(i)}_{L\,x\,1}^{g,c}$associated with the *neurons*, the row-vectors of $\boldsymbol{LW(N')}^{G,c}$ that changed after *class training*, and it is clear that $L' < L$.

Finally, it operated *class assignment*, whose outline is shown in Figure 3. This linear layer took $\boldsymbol{LW(N')}^{F,c}$ and $\boldsymbol{X2}^c$ as inputs. It was set as $j = 1$, and the *neuron* $_{e'}\boldsymbol{LW(N')}^{F,c}$ closest to $_j\boldsymbol{X2^c}$ was identified, where $e' = \arg \min_l \left\{\left\|_j\boldsymbol{X2}^c - {}_l\boldsymbol{LW(N')}^c\right\|\right\}, l \in \{1, \dots, L'\}$ in an analogous process performed in *step (ii)* in the *training class*; and then it was assigned to a $_j\boldsymbol{X2^c}$**,** using A function, the same classification $_{e'}\boldsymbol{LW(N')}^{F,c}$. If $j + 1 \le N''$ was made $j = j + 1$, the *class assignment* was repeated; otherwise, it was stopped. At the end of this iterative process of j, a new column-vector of classifications for the row vectors of $\boldsymbol{X2}^c$ resulted, named $\boldsymbol{LVQ}_c{}^{L,G}$. Then, if $c + 1 \le 495$, it was made $c = c + 1$ and repeated from *step 3*; otherwise, it stopped. The result at the end of the iterative process of c was $\boldsymbol{LVQ}_{N''x\,495}{}^{L,G}$, whose column-vectors $\left\{\boldsymbol{LVQ}_c{}^{L,G}\right\}_{c=1}^{495}$ represent the reassignment classes using $\boldsymbol{X1}^c$ for *class training*. The general outline of *step 3* is shown in Figure 4.

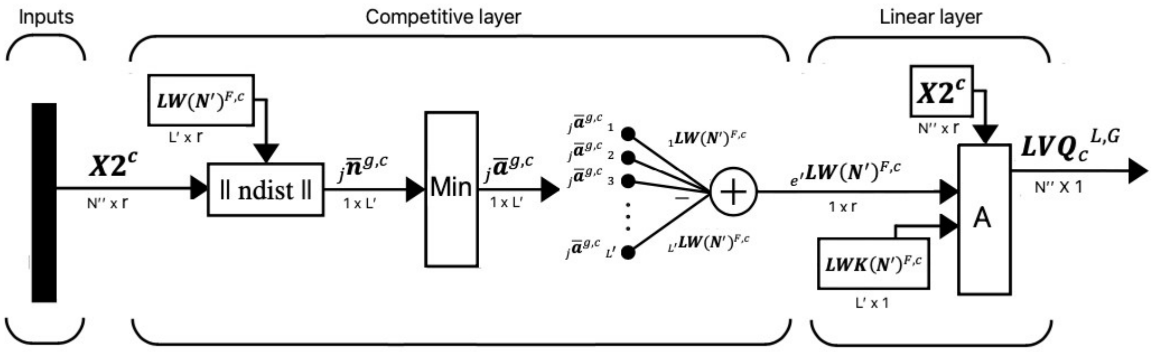

Figure 3. General outline of the class assignment. The class assignment has a competitive layer and a linear layer. Source: own elaboration.

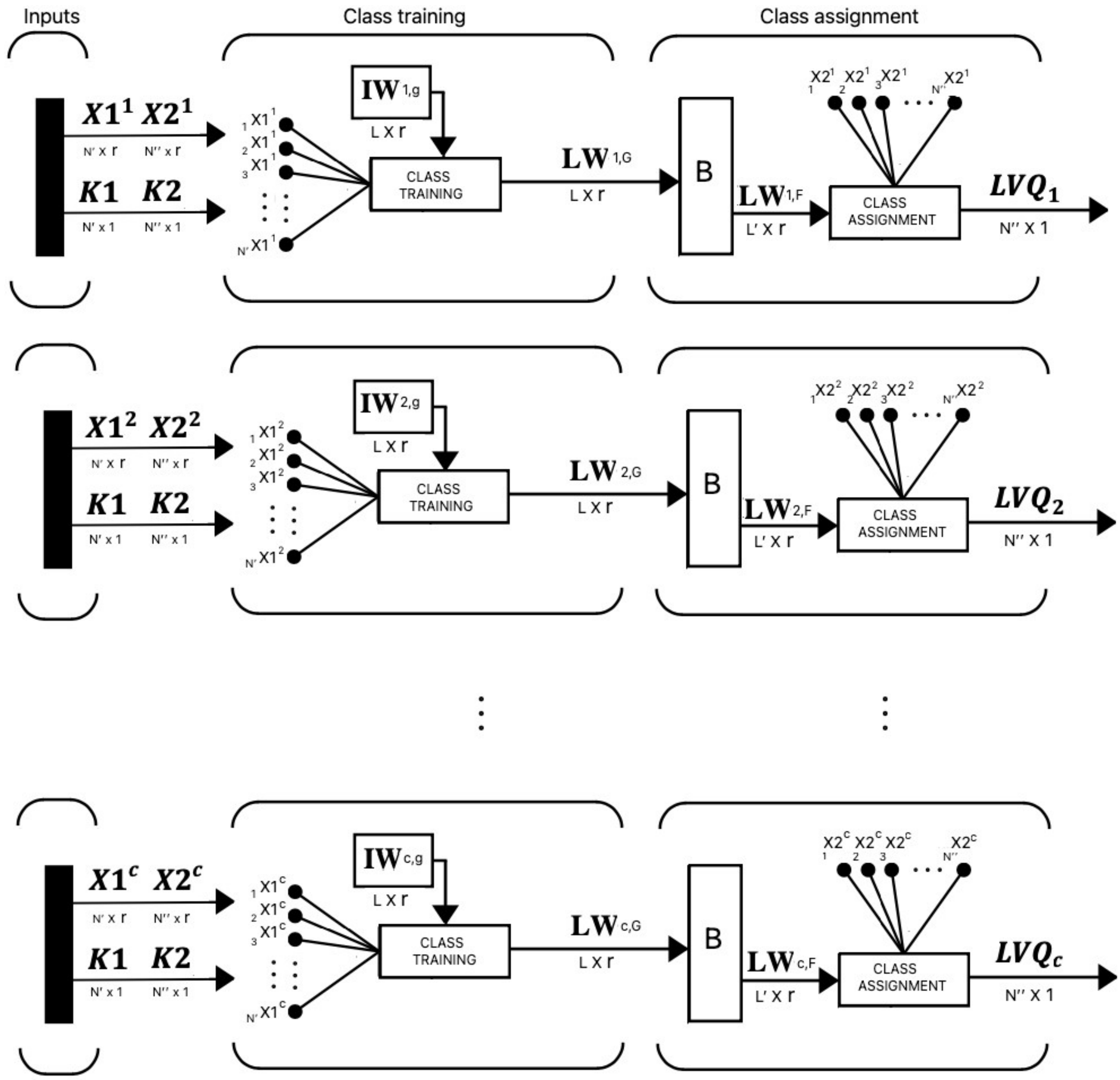

Figure 4. General outline of *step 3* of the HC-LVQ Artificial Neural Network. Source: own elaboration.

Step 4. C*lass validation* operated by the V function. Once $\boldsymbol{LVQ}^{L,G}$ was obtained, by the statistical test of the Accuracy Rate (ACC)[14], each $\{\boldsymbol{LVQ}_c\}_{c=1}^{495}$ was evaluated by comparing it with the Bry-Boschan classification $\boldsymbol{K2}$. Finally, the HC-LVQ algorithm selected the optimal class reassignment column-vector $\boldsymbol{LVQ}_{óptimo}^{L,G}$ renamed $\boldsymbol{HC\text{-}LVQ}^{\ L,G}$, which maximized ACC. Additionally, the Brier Score (QPS)[15], Sensitivity[16], and Specificity[17] were calculated for $\boldsymbol{HC\text{-}LVQ}^{\ L,G}$, also by comparing it with the Bry-Boschan classification $\boldsymbol{K2}$. Then, the indicators or stock market indexes associated with $\{\boldsymbol{X1}^{pptimal}\}^{L,G}$ ere obtained. Both results were associated with the initial parameters L and G. The general outline of steps 1, 2, 3, and 4 of HC-LVQ is shown in Figure 5.

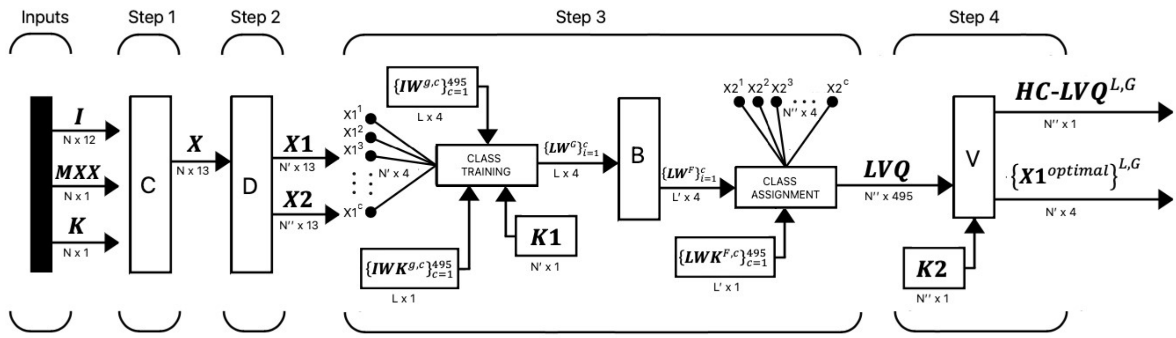

Figure 5. General outline of *steps 1*, *2*, *3,* and *4* of the HC-LVQ Artificial Neural Network. Together, these steps produced the $\boldsymbol{HC\text{-}LVQ}^{\ L,G}$ vector corresponding to the forecast made by the HC-LVQ of the classifications for the second time period of the $\boldsymbol{MXX}$, as well as the set of optimal series corresponding to $\{\boldsymbol{X1}^{optimal}\}^{L,G}$. Source: own elaboration.

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[14] A good result maximizes the ACC and, in turn, minimizes QPS, due to the relationship between these two statistical measures.

[15] The QPS is an appropriate scoring function that measures the accuracy of probabilistic predictions. For unidimensional predictions, it is strictly equivalent to the mean square error. Relevant for binary results, such as those obtained in this work, and categorical results that can be structured as true or false, it is defined as follows:

$$QPS = \frac{1}{N}\sum_{n=1}^{N}\left(\hat{E}_n - E_n\right)^2$$

where $n = 1, \dots,\ N$ is the number of forecast. $\hat{E}_n$ is the forecast made by the model used, and E_n is the true result. The QPS is, in itself, the sum of the mean square errors. In each iteration, a result of 0 is the best possible, while 1 is the worst possible. A more effective model aims to minimize the QPS.

[16] The Sensitivity of a test represents the probability that a true positive will be correctly classified. In the particular case of this study, it represents the correctly classified *bull cycles*.

$$Sensitivity = \frac{T_p}{T_p + F_n}$$

where T_p are the true positives, and F_n are the false negatives, i.e., incorrectly classified *bear cycles.* When multiplied by 100, this measure represents the percentage of correctly classified *bull cycles*.

[17] The specificity of a test represents the probability that a negative, *bear cycle*, will be correctly classified. When multiplied by 100, this measure represents the percentage of *bear cycles* correctly classified.

$$Specificity = \frac{T_n}{T_n + F_p}$$

where T_n are the true negatives, and F_p are the false positives.

Step 5. Finally, in this step, which is observed in Figure 6, the optimal neuron matrix $\boldsymbol{LW}\left(\boldsymbol{N}'\right)^{F,optimal}$ associated with $\boldsymbol{HC\text{-}LVQ}^{\ L,G}$ was identified, and then *class assignment* was applied for $\boldsymbol{LW}\left(\boldsymbol{N}'\right)^{F,optimal}$ and $\{\boldsymbol{X1}^{optimal}\}^{L,G}$. The result was the column-vector $\boldsymbol{HC\text{-}LVQ1}^{\ L,G}$, whose N'-inputs corresponded to the class reassignment for the first time period of the $\boldsymbol{MXX}$. This reassignment was also evaluated using ACC, the QPS, Sensitivity, and Specificity by comparing the Bry-Boschan classification$\boldsymbol{K1}$ with $\boldsymbol{HC\text{-}LVQ1}^{\ L,G}$, obtaining the corresponding $acc1^{L,G}$, $qps1^{L,G}, S1^{L,G}$ y $E1^{L,G}$ values. Finally, the HC-LVQ obtained outputs: The optimal set of series, represented by $C(opt.,:)^{L,G}$, as well as the $\boldsymbol{HC\text{-}LVQ1}^{\ L,G}$ and $\boldsymbol{HC\text{-}LVQ}^{\ L,G}$ forecasts of the MXX; and their corresponding statistical measures: $acc1^{L,G}$, $qps1^{L,G}, S1^{L,G}$ y $E1^{L,G}$; y $acc^{L,G}$, $qps^{L,G}, S^{L,G}$ y $E^{L,G}$; all for the first and second time periods, respectively.

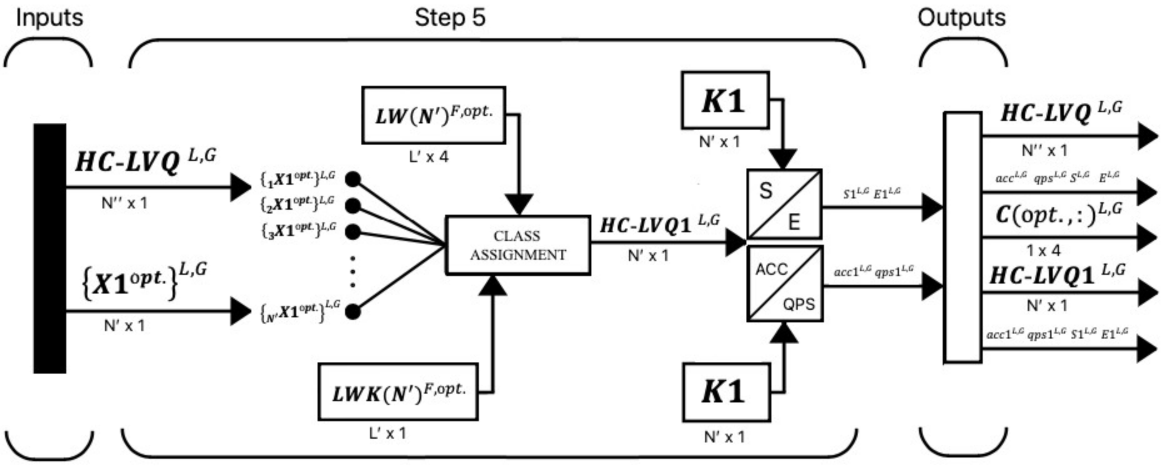

Figure 6. Outline of *step 5* and the outputs of the HC-LVQ Artificial Neural Network. Source: own elaboration.

The HC-LVQ Artificial Neural Network was implemented 110 times, first varying the number of *neurons* from de $L = 10: 10: 100$, and for each value of L, parameter G of the number of *epochs* varied: First $G = 5$ and then $= 10: 10: 100$. The HC-LVQ methodology can be summarized in the following steps:

1. The inflection points of the target time series, the MXX, and its indicators $I_{N\,x\,12}$, the selection of 12 stock market indexes, for the complete period, from January 1993 to January 2024, were identified using the Bry-Boschan algorithm (1971). This yielded the vector X_{13} of Bry-Boschan classifications for the MXX.

2. The HC-LVQ Neural Network was implemented for each pair of parameters (L,G), varying the number of *neurons* from 10 to 10, from $L = 10$ to 100, and for each value L, parameter G of the number of epochs varied, first $G = 5$ and then $G = 10$ up to 100, also from 10 to 10, as can be seen in Figure 7. In each implementation, the network took the group of four stock indexes from each of the 495 possible combinations, as well as the MXX index, to implement the LVQ Neural Network in a chain.

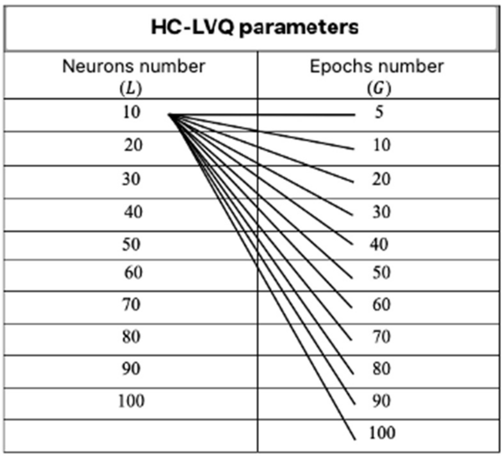

Figure 7. This figure shows the combinations of the parameter pair (L, G) used in each implementation of the HC-LVQ. Source: own elaboration.

3. Results and discussion

The set optimal of four key stock market indexes of indicators of the Mexican financial cycle based on the MXX, indicated by the HC-LVQ method, were the Chinese HANG SENG, the German DAX 40, the Brazilian BOVESPA, and the SPIPSA of Santiago de Chile. This result suggested the existence of an intrinsic interconnection between the joint movement of these four financial cycles, based on the stock indexes of the major stock markets of China, Germany, Brazil, and Chile (CABC) and the behavior of the Mexican financial cycle. The historical price movements of these indexes and the MXX during the complete study period are shown in Figure 8.

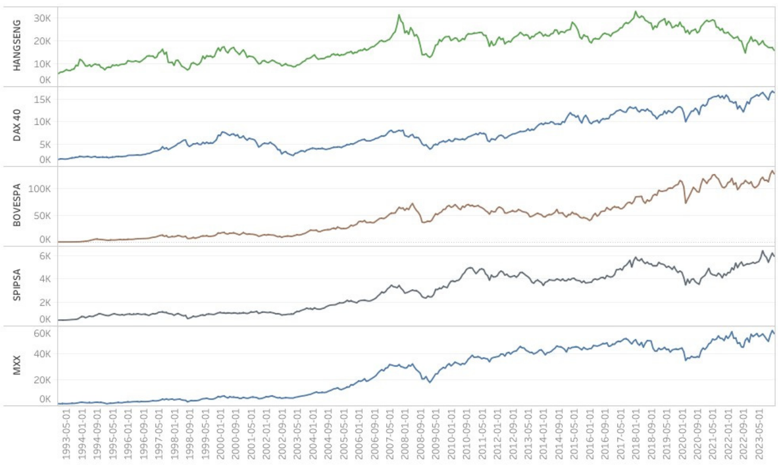

Figure 8. Historical price movements of the CABC and MXX indexes during the study period. Source: own elaboration.

This intrinsic relationship can be explained by the simplicity and philosophy of the HC-LVQ method, in which no prior financial considerations were made except for the origin of the financial data set used. HC-LVQ identified the optimal *neurons*, represented as $\boldsymbol{LW}(\boldsymbol{N'})^{F,optimal}$, which define class regions in the data input space and are invariant over time, remaining, by construction, in those regions at any given moment. Furthermore, these neurons optimize the classification of data in the test period, simply following the nearest neighbor rule to assign the classification of incoming data. The corresponding optimal parameters found by HC-LVQ were 40 neurons (L) and 5 epochs (G); the analysis is presented later in this section.

This result also coincides with the overwhelming data that the Chinese economy has been recording for decades, especially since 2012, added to the evidence reported in the literature by Clayton et al. (2023) and Cortina et al. (2023) on the increasingly prominent role that China is playing in global business cycles, economically and financially, becoming the largest global economic power in 2024, in terms of the adjusted GDP, with a 19% share, compared to 15.2% for the United States. Moreover, China's share of Mexico's international purchases has been steadily increasing over the last 18 years, reaching just over 20% in 2023, making it the second-largest supplier after United States. This, added to the geopolitical context and the decoupling of the US economy from China, creates a critical moment, not only economically but also financially for Mexico.

Furthermore, it is not a surprise that the Brazilian and Chilean stock market indexes are signaled by HC-LVQ as indicators of the Mexican financial cycle, not only because of the macroeconomic data showing that Brazil and Chile are among Mexico's major trading partners, with Mexico also having a trade deficit with them, but also because of the vast literature on the subject, including researchers such as Modi et al. (2010), Forbes et al. (1999), Arouri et al. (2013), and Bekaert and Harvey (2000), which demonstrates the existence of cointegration between the main stock market indexes of Mexico and South America, where Mexico appears to play a leading role and be a pole of financial influence in the Latin American region.

In the case of Germany's DAX added to the evidence in the literature presented above, which highlights data on this country, the interaction between the German and Mexican financial cycles has not been sufficiently studied in terms of their cycles based on their major stock market indexes. However, Germany's participation in Mexico's economy is undeniable, as it was Mexico's fourth largest trading partner in 2023.

Together, these four countries, CABC, accounted for around 7.4% of Mexico's exports and 26.4% of Mexico's imports in 2023. Excluding the United States and Canada, CABC accounted for around 46% of the volume of trade between Mexico and other countries.

On the other hand, regarding the identification of the inflection points of the Mexican financial cycle, the HC-LVQ outperformed the Bry-Boschan algorithm (1971), as shown in Figure 9 and Table 1, for the identification of all the *bear* points of the MXX during the *test period*. In particular, the HC-LVQ and the Bry-Boschan algorithm agreed in the identification of a *bear* point in 2017, which coincides, moreover, with the slowdown of the Mexican economy that year, where the Mexican Gross Domestic Product (GDP) grew 2.0%, almost 1% below 2016. It is important to note that the HC-LVQ advanced the identification of the *bear* of the *Subprime* crisis by 5 months compared to the BryBoschan algorithm (1971), identifying the *bear* in May 2007 and the *bull* in August 2008. This contrasts with the SICCA, which identified the peak of the *Subprime* crisis for the Mexican business cycle in April 2008 and in June 2009 its recovery; and the NBER, which identified the peak of the *Subprime* crisis of the U.S. business cycle in December 2007 and in June 2009 the trough.

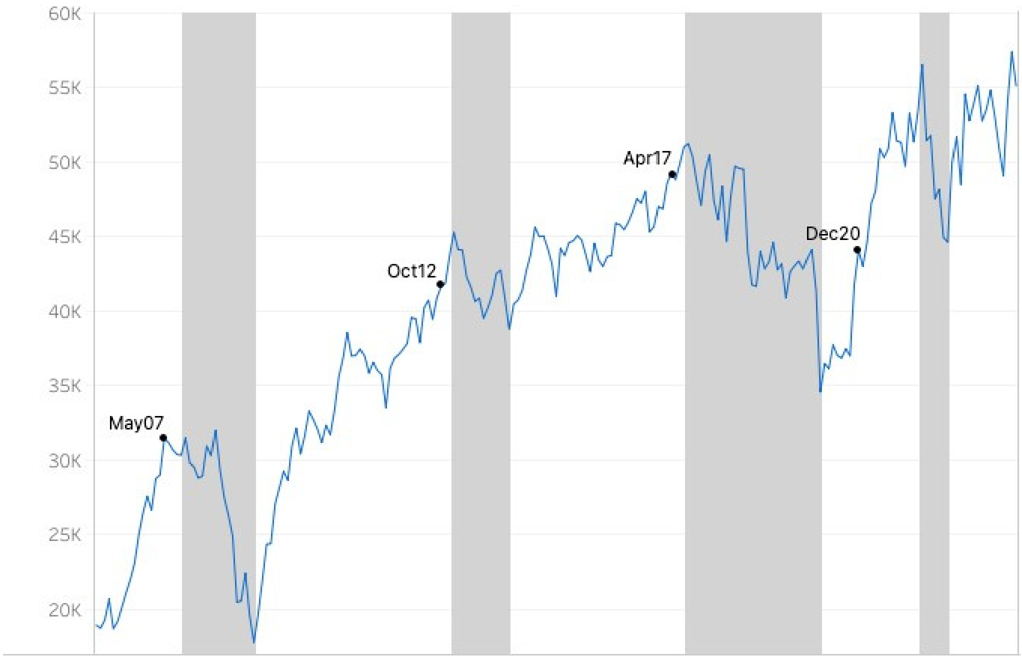

Figure 9. Comparison between the *bear* and *bull points* of the Mexican financial cycle, based on the MXX, identified by HC-LVQ, whose bear points are shown in black; and those identified by the Bry-Boschan algorithm, whose *bear cycles* are shaded. The period covers January 2006 to January 2024. It can also be seen that the HC-LVQ identifies the *bear* of the Subprime crisis 5 months ahead of the Bry-Boschan algorithm, identifying it in May 2007 and the *bull* in August 2008. Source: own elaboration.

Table 1. Dating results of the Mexican financial cycle based on the MXX using the HC-LVQ methodology and the Bry-Boschan algorithm (1971), respectively.

Crisis		Financial cycles MXX (HC-LVQ)		MXX (Bry-Boschan)	
Year	Name	Peak	Trough	Peak	Trough
1994	Tequila effect	-	-	sep-94	feb-95
1997	Asian and Russian crisis	apr-98	aug-98	sep-97	aug-98
2001	dot.com	oct-99	jun-01	apr-02	sep-02
2007	Subprime	may-07	aug-08	oct-07	feb-09
2013	Ukrainian crisis	oct-12	jul-15	jan-13	feb-14
2017	*	apr-17	aug-19	aug-17	mar-20
2020	Covid-19	dec-20	may-21	mar-22	sep-22

It can be seen that the HC-LVQ artificial neural network identified all the *bear* of the Bry-Boschan algorithm, during training and test periods; except for the September 1994 *bear.* In addition, its dates were ahead of the Bry-Boschan algorithm (1971), identifying all the *bear* in the test period; in particular, for the *bear* of the Subprime crisis the, HC-LVQ was ahead of the Bry-Boschan by 5 months, identifying the *bear* of the beginning of the Subprime crisis in May 2007, and the *bull*, the end of the crisis, in August 2008. * The peaks indicated by both algorithms in 2017 coincide with the slowdown in the Mexican economy that year. Source: own elaboration.

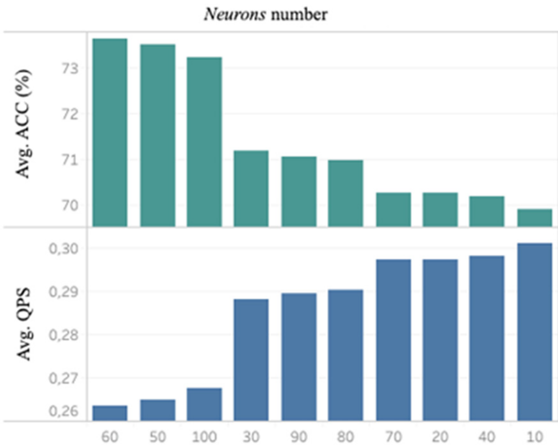

Figure 10. Average ACC and QPS for each value L of the neurons in the class validation over the test period. It can be observed that the number L=60 neurons is the one that maximizes the ACC with a value of 73,65% and minimizes the QPS with a value of 0,264. Source: own elaboration.

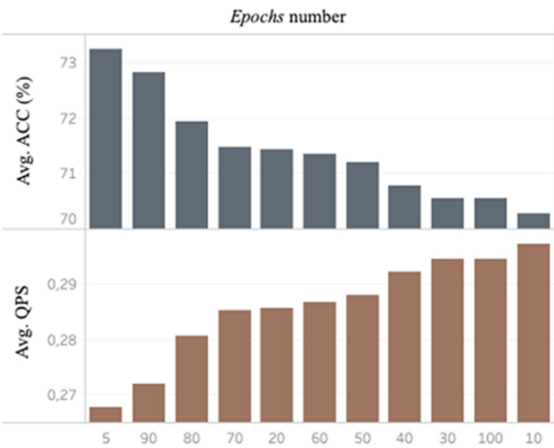

Figure 11. Average ACC and QPS for each G value of epochs in the class validation over the test period. It can be observed that the number G=5 epochs is the one that maximizes the ACC with a value of 73,23% and minimizes the QPS with a value of 0,267. Source: own elaboration.

The results presented above were obtained after analyzing the results of the 110 implementations of the HC-LVQ Artificial Neural Network; for the class validation of the MXX over the test period, from January 2006 to January 2024; comparing the Bry-Boschan classification K2 and the reassigned HC-〖LVQ〗^(L,G), for each value of the number of neurons L, averaged over the values of the number of epochs G; and an Accuracy Rate (ACC) above 70% and a QPS below 0,30, were obtained, except for L=10, where an ACC of 69,88% and a QPS of 0,301were obtained. Similarly, as shown in Figure 10, for values of the number of neurons L=50,60, and 100, the HC-LVQ obtained an average ACC above 73,23%, and a QPS below 0,27. In particular, the number L=60 neurons maximized the ACC and minimized the QPS with values of 73,65% and 0,264, respectively. Likewise, class validation over the test period yielded an average ACC above 70,28% for each value of G averaged over the values of the number of neurons L, as shown in Figure 11. For values of G=5 and 90, the HC-LVQ obtained an average ACC above 72,8% and an average QPS below 0,282. In particular, the number G=5 of epochs maximized the ACC and minimized the QPS with values of 73,23% and 0,267, respectively.

Regarding *class validation* on the *learning period*, from January 1993 to December 2005, comparing the Bry-Boschan classification $\boldsymbol{K1}$ and the reassigned $\boldsymbol{HC\text{-}LVQ1}^{l,g}$, the HC-LVQ obtained, for each value of the *neurons (L)*, averaged across the values of the number of *epochs* (G). The average ACC was above 82,23%, and the values of *neurons* that maximized ACC were $L = 50{,}60{,}90$, and 100, obtaining an average ACC above 90,74%, and an average QPS below 0,093, as shown in Figure 12. In contrast, for low values of $L = 10{,}20{,}30$, *neurons* obtained ACC values below 84,5% and QPS values above 0,15. In particular, the value of $L = 100$ for *neurons* was the one that maximized the ACC and minimized the QPS with values of 91,14% and 0,088, respectively.

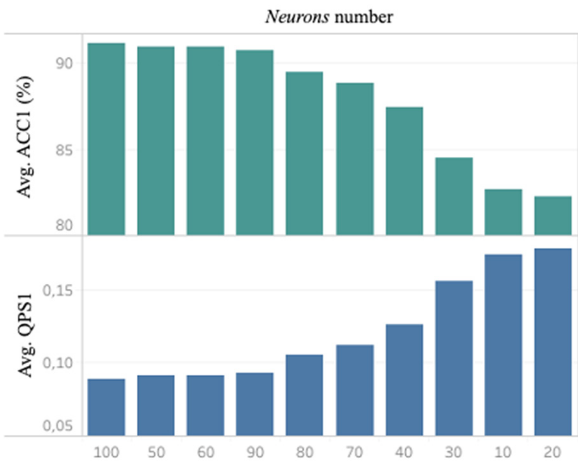

Figure 12. Average ACC and QPS for each value L of neurons in the class validation over the training period. It can be observed that the number L=100 of neurons is the one that maximized the ACC with a value of 91,14% and minimized the QPS with a value of 0,088. Source: own elaboration.

The results of the *class validation* on the *learning period* showed that for each value of *epochs* (G), on average, of the values of the number of *neurons* (L), an average ACC above 85,71% was obtained, as shown in Figure 13. For values of $G = 80\ and\ 90$, the HC-LVQ obtained an average ACC above 89% and a QPS below 0,11. in particular, the number $G = 80$ of epochs is the one that maximized the ACC and minimized the QPS with values of 89,34% and 0,106, respectively.

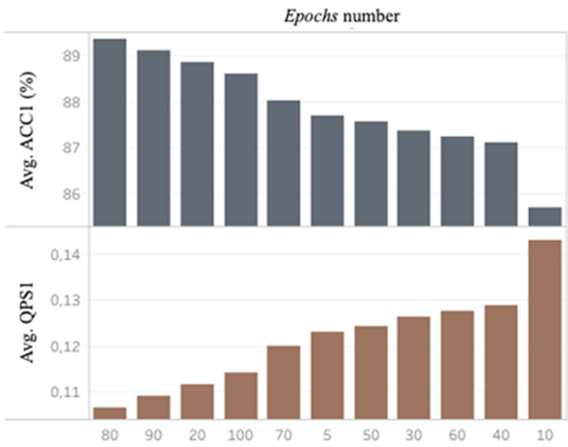

Figure 13. Average ACC and QPS for each G value of epochs in the class validation over the test period. It can be observed that the number G=5 epochs is the one that maximizes the ACC with a value of 73,23% and minimizes the QPS with a value of 0,267. Source: own elaboration

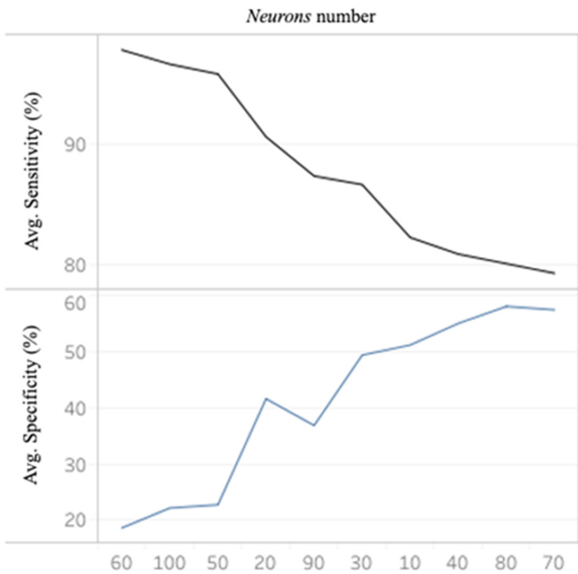

Figure 14. Average Sensitivity and Specificity, over the test period, for each L value of neurons averaged over the number of epochs. It can be seen that the increase in Sensitivity beyond 81% drastically reduces the percentage of correctly identified bear points. Source: own elaboration.

Furthermore, in the search for the optimal set of the four key stock market indexes or indicators that best helped identify the *bear* and *bull cycles* of the Mexican financial cycle, an analysis of the Sensitivity was made of the results over the *test period*. The Sensitivity measured the percentage of *bull cycles* that were correctly identified by the HC-LVQ; and of the Specificity that measured, the percentage of *bear cycles* was correctly identified by the network. Thus, it was observed, as shown in

Figure 14, that for each value of the number of *neurons (L)*, averaged across the value of the number of *epochs (G)* and the value of Sensitivity increased beyond 81%, the value of Specificity was drastically reduced; in other words, as the percentage of correctly identified *bull cycles* increased, the percentage of correctly identified *bear cycles* was reduced. In this case, $L = 40\ and\ 80$ were the values of the number of *neurons* that exceeded the average number of *epochs (G)*, with 55% correctly identified *bear cycles*, and about 80,5% of correctly identified *bull cycles*. Additionally, it could be observed that for values of L = 50,60 and 100, in contrast to a good performance for ACC shown in Figure 12, these L values, on average for G values, presented a poor performance for Specificity, below 22,73%.

Similarly, as shown in Figure 15, for each value of the number of *epochs* (G), averaged across the values of the neurons (L), the increase in Sensitivity was also related to the decrease in Specificity, except for $G = 5$, which did not follow the trend and where, on average, a Specificity of 47,33% and a high Sensitivity of 87,05% were obtained. In this tenor, we searched for the result that optimized not only the ACC and QPS values, meaning maximizing the ACC and minimizing the QPS, but also optimizing, in turn, the Sensitivity and Specificity values, and maximizing the percentage of correctly identified *bear* points with a Sensitivity value between 75% and 80,5%.

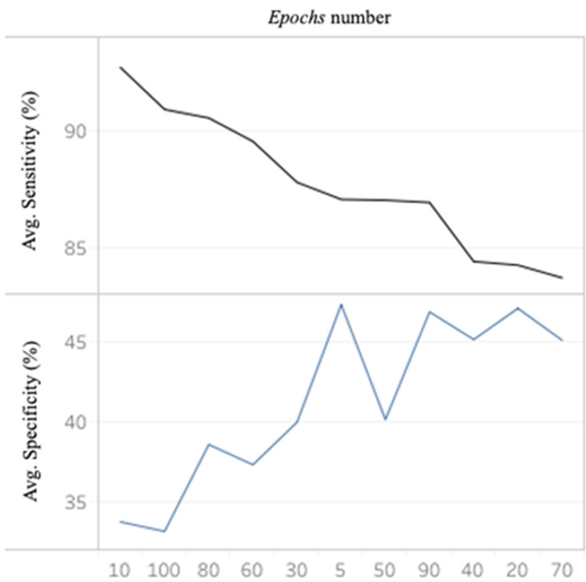

Figure 15. Average Sensitivity and Specificity, over the test period, for each G value of the number of epochs, averaged over the number of neurons. It can be seen that the increase in average Sensitivity is also related to the decrease in Specificity, except with G=5, which does not seem to follow this trend. Source: own elaboration.

Thus, it was found that the combination $c_{opt.} = 368$ of stock market indexes, whose parameters were $L = 40\ and\ G = 5$, was the one that optimized the set of statistical tests for the *test period* by obtaining an ACC of $acc_{opt.} = 75{,}12\%$. For the QPS, a value of $qps_{opt.} = 0{,}249$; for the Sensitivity, a value of $S_{opt.} = 76{,}38\%$; and for Specificity, a value of $E_{opt.} = 73{,}33\%$. Additionally,for the *learning period*, an ACC of $acc1_{opt.} = 85{,}9\%$ was obtained; for the QPS, a value of $qps1_{opt.} =$

$0{,}141$ was obtained; for the Sensitivity, a value of $S_{opt.} = 96{,}67\%$ was obtained; and for the Specificity, a value of $E_{opt.} = 50$ was obtained.

4. Conclusions

The set of four key stock market indexes that best helped identify the turning points of the Mexican financial cycle, based on the MXX, were the Chinese HANG SENG, the German DAX 40, the Brazilian BOVESPA, and the SPIPSA of Santiago de Chile, confirming China's increasingly prominent role in Mexican business cycles and suggesting the existence of an intrinsic interconnection between the Mexican financial sector and the major stock markets of its most important trading partners. In the case of South American indexes, this could also suggest an intrinsic interconnection between financial sectors. It should be noted that other important trading partners in the region, such as Peru, Colombia, and Guatemala, were excluded from the study due to a lack of data, in addition to computational limitations to include at least the main index of each of Mexico's twenty major trading partners. None of the three US stock market indexes were considered among the initial selection of 12 indexes: The NASDAQ Composite, the NYSE Composite, or the S&P 500 appeared in the optimal set, despite expectations of a more relevant role as indicators of the MXX, given that numerous studies affirm that stock market integration in North America has increased since the signing of NAFTA in 1994.

The HC-LVQ Artificial Neural Network proved to be a competitive method compared to other traditional methods in identifying turning points in the Mexican financial cycle, outperforming the Bry-Boschan algorithm (1971) in identifying all *bear* points in the *test period*, from January 2006 to January 2024. In particular, the HC-LVQ identified the *bear* (peak) of the *Subprime* crisis five months earlier than the Bry-Boschan algorithm, identifying the onset of the crisis in May 2007 and its recovery in August 2008, thereby highlighting the relevance of the non-classical approach to studying financial cycles. With this, the HC-LVQ also confirmed that the peak of the *Subprime* crisis in Mexico preceded the peak of the economic crisis, as the SICCA indicated the peak of the Mexican economic cycle in April 2008 and its recovery in June 2009, while the NBER identified the peak of the *Subprime* crisis in the US economic cycle in December 2007 and the trough in June 2009.

The HC-LVQ has computational advantages, inherited and optimized from the LVQ method[18], over parametric methods that have been frequently used to identify business cycle turning points based on a set of coincident indicators. Moreover, it is very easy to implement, and a large number of indicators can be incorporated, even with reports of different frequencies. The HC-LVQ method is, by its origin, a method to solve statistical classification problems such as the one presented in this paper, which, added to our results, makes it an attractive and competitive method in several areas and not only in Finance or Economics, where a problem can be reduced to a statistical classification problem. We focused on the Mexican financial cycle, but the method is easily adaptable to other economies, extending to different financial systems.

The values of the parameters $L = 40$ number of *neurons* and $G = 5$ number of *epochs* were the ones that optimized the HC-LVQ method. This pair optimized the statistical test set for the *test period*

[18] More than 54,000 applications of the LVQ Artificial Neural Network were achieved, compared to around 100 implemented by Giusto and Piger (2014).

by obtaining an ACC of $acc_{opt.} = 75{,}12\%$; for the QPS: A value of $qps_{opt.} = 0{,}249$; for the Sensitivity: A value of $S_{opt.} = 76{,}38\%$; and for Specificity: A value of $E_{opt.} = 73{,}33\%$. Moreover, for the *learning period*, an ACC of $acc1_{opt.} = 85{,}9\%$ was obtained; for the QPS, a value of $qps1_{opt.} = 0{,}141$ was obtained; for Sensitivity, a value of $S_{opt.} = 96{,}67\%$ was obtained; and for Specificity, a value of $E_{opt.} = 50\%$ was obtained.

Finally, the results of this study and the extensive literature consulted and summarized herein have demonstrated not only the need to study the Mexican financial cycle, but also the need to generate and store data on the Mexican financial sector to facilitate its study and analysis. All of this is necessary to counteract the effects that fluctuations in the financial sector have on the real Mexican economy.

Author contributions

Author Jonathan Moisés Ramírez Bautista (The Worker): Conceptualization (Lead), Data Curation (Lead), Formal Analysis (Lead), Funding Acquisition (Lead), Investigation (Lead), Methodology (Lead), Project Administration (Lead), Resources (Lead), Software (Lead), Supervision (Lead), Validation (Lead), Visualization (Lead), Writing – Original Draft (Lead), Writing – Review & Editing (Lead). Author Federico Hernández Álvarez (The Advisor): Conceptualization (Supporting), Formal Analysis (Supporting), Supervision (Lead), Writing – Original Draft (Supporting), Writing – Review & Editing (Supporting).

All authors have read and approved the final manuscript.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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